

Predicting the Next Location:  
A Recurrent Model with Spatial and Temporal Contexts

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# Problem Formulation

- Task is to predict where a user will go next at a specific time  $t$ .
- $P$  : set of users
  - $p_u \in R^d$  : latent vectors of user  $u$
- $Q$  : set of locations
  - $q_v \in R^d$  : latent vectors of location  $v$
- $v = \{x_v, y_v\}$
- $Q^U = \{Q^{u_1}, Q^{u_2}, \dots\}$
- $Q^u = \{q_{t_1}^u, q_{t_2}^u, \dots\}$

# Recurrent Neural Networks

$$\mathbf{h}_{t_k}^u = f \left( \mathbf{M} \mathbf{q}_{t_k}^u + \mathbf{C} \mathbf{h}_{t_{k-1}}^u \right)$$

- $h_{t_k}^u$  : representation of user  $u$  at time  $t_k$
- $C$  : recurrent connection of the previous status propagating sequential signals
- $M$  : transition matrix
- $f$  : sigmoid

# RNN with Temporal Context

$$\mathbf{h}_t^u = f \left( \sum_{q_{t_i}^u \in Q^u, t-w < t_i < t} \mathbf{T}_{t-t_i} \mathbf{q}_{t_i}^u + \mathbf{C} \mathbf{h}_{t-w}^u \right)$$

- $w$  : width of time window
- $T_{t-t_i}$ : time-specific transition matrix ( current time  $t$  )

# Spatial Temporal Recurrent Neural Networks

$$\mathbf{h}_{t, q_t^u}^u = f \left( \sum_{q_{t_i}^u \in Q^u, t - \hat{w} < t_i < t} \mathbf{S}_{q_t^u - q_{t_i}^u} \mathbf{T}_{t - t_i} \mathbf{q}_{t_i}^u + \mathbf{C} \mathbf{h}_{t - \hat{w}, q_{t - \hat{w}}^u}^u \right)$$

- $S_{q_t^u - q_{t_i}^u}$ : distance-specific transition matrix
- geographical distance

$$q_t^u - q_{t_i}^u := \|x_t^u - x_{t_i}^u, y_t^u - y_{t_i}^u\|_2$$

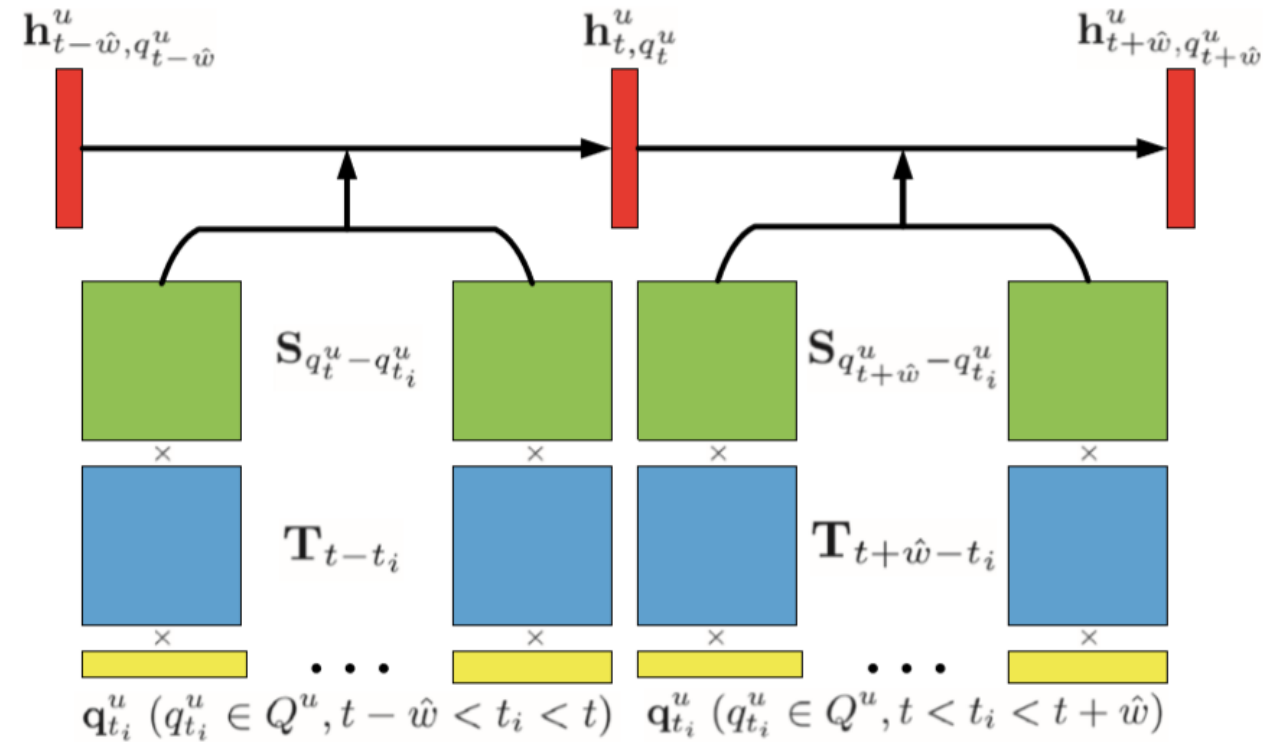
- Not exist the location user  $u$  visits at time  $t - w$  in the visiting history  $Q^u$ 
  - Approximate value  $\hat{w}$ : the most closed value to  $w$

# ST-RNN (cont'd)

- Prediction

$$o_{u,t,v} = (\mathbf{h}_{t,q_v}^u + \mathbf{p}_u)^T \mathbf{q}_v$$

- $p_u$  : permanent presentation of user  $u$



# Linear Interpolation for Transition Matrices

- Data sparsity problem
  - Partition time interval and geographical distance into discrete bins
  - Transition matrices can be calculated via a linear interpolation

$$\mathbf{T}_{t_d} = \frac{[\mathbf{T}_{L(t_d)}(U(t_d) - t_d) + \mathbf{T}_{U(t_d)}(t_d - L(t_d))]}{[(U(t_d) - t_d) + (t_d - L(t_d))]},$$

$$\mathbf{S}_{l_d} = \frac{[\mathbf{S}_{L(l_d)}(U(l_d) - l_d) + \mathbf{S}_{U(l_d)}(l_d - L(l_d))]}{[(U(l_d) - l_d) + (l_d - L(l_d))]},$$

# Parameter Inference

- User prefers a selected location than a negative one

$$p(u, t, v \succ v') = g(o_{u,t,v} - o_{u,t,v'})$$

- $v'$  : negative location sample
- $g(x) = 1/(1 + e^{-x})$

- Negative log likelihood

$$J = \sum \ln(1 + e^{-(o_{u,t,v} - o_{u,t,v'})}) + \frac{\lambda}{2} \|\Theta\|^2$$



# Experimental Settings

- Gowalla

[user]	[check-in time]	[latitude]	[longitude]	[location id]
196514	2010-07-24T13:45:06Z	53.3648119	-2.2723465833	145064
196514	2010-07-24T13:44:58Z	53.360511233	-2.276369017	1275991
196514	2010-07-24T13:44:46Z	53.3653895945	-2.2754087046	376497
196514	2010-07-24T13:44:38Z	53.3663709833	-2.2700764333	98503
196514	2010-07-24T13:44:26Z	53.3674087524	-2.2783813477	1043431
196514	2010-07-24T13:44:08Z	53.3675663377	-2.278631763	881734
196514	2010-07-24T13:43:18Z	53.3679640626	-2.2792943689	207763
196514	2010-07-24T13:41:10Z	53.364905	-2.270824	1042822

- Recall@k
- F1-Score@k
- Mean Average Prediction (MAP)
- ROC curve (AUC)